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EXCELENCIA SEVERO OCHOA

Summer predictions of sea ice edge and the link between autumnal Arctic sea ice and Northern Hemisphere winter forecast skill

J.C. Acosta Navarro, L. Batté, P. Ortega, D. Smith, P.A. Bretonnière, V. Guemas, F. Massonnet, V. Sicardi, V. Torralba, E. Tourigny and F.J. Doblas-Reyes, Ilona Välisuo and Matthieu Chevallier

9/1/2020

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Seasonal forecast system configuration

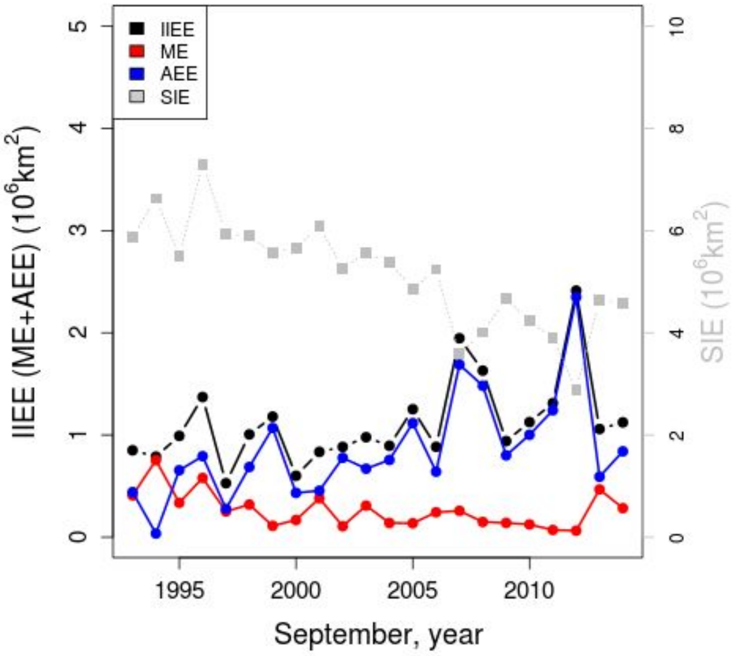
Model/System	CNRM-CM6-1	EC-Earth 3.2.2	SEAS5	GloSea5	MF-Sys6
Atmosphere	ARPEGE 6.3	IFS Cy36r4	IFS Cy43r1	UM v6	ARPEGE 6.2
Ocean	NEMO 3.6	NEMO 3.6	NEMO 3.4	NEMO 3.4	NEMO 3.6
Sea ice	GELATO v6	LIM3	LIM2	CICE 4.1	GELATO v6
Atmospheric resolution	tl127l91r (~ 1.4°)	tl255l91r (~ 0.7°)	tCo319L91	N216L85	tl359l91r (~0.5°)
Ocean resolution	eORCA1 L75	ORCA1L75	ORCA 0.25 L75	ORCA 0.25 L75	eORCA 1 L75
Sea ice initial conditions	GELATO-NEMO run constrained towards GLORYS 2V4 (Mercator)	Forced LIM3-NEMO run with ENKF SIC assimilation	ORA-S5	NEMOVAR	GELATO-NEMO run constrained towards GLORYS 2V4 (Mercator)
Ensemble size	30	10 May and 25 Nov	25	28*	25*

*Characteristics of the seasonal re-forecasts evaluated. All systems are initialized with ERA-Interim for the atmosphere component. * All re-forecasts are initialized on the 1st of the month, except for GloSea5 for which 7 members from the 9th, 17th and 25th of April as well as 7 from the 1st of May are grouped into a 28-member ensemble, and MF-Sys6 for which 12 members from the 20th and 25th of April are grouped with one member from the 1st of May*

Integrated Ice-Edge Error (IIEE)

- In the Multi-model ensemble, most of the IIEE is due to extent error

- During the re-forecast period, IIEE tends to grow → most models overestimate total SIE at the end of the period and underestimate linear trends



September 1993-2014 IIEE and decomposition (ref : NSIDC) in the 5-model MME re-forecast. Gridpoint SIC is bias-corrected for each model before computation of IIEE.

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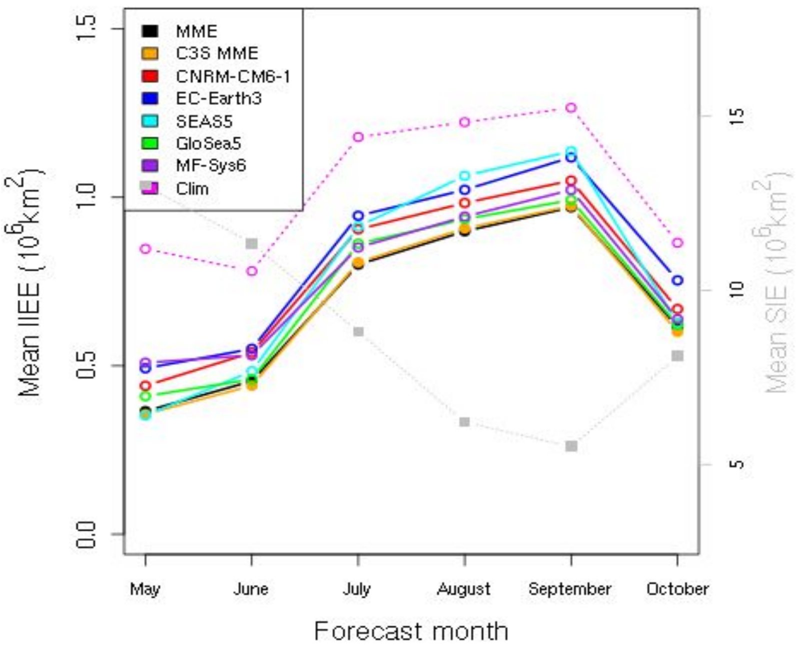
Integrated Ice-Edge Error (IIEE)

- After trend-adjusting gridpoint SIC, all models show lower IIEE than a linear trend climatology (magenta).

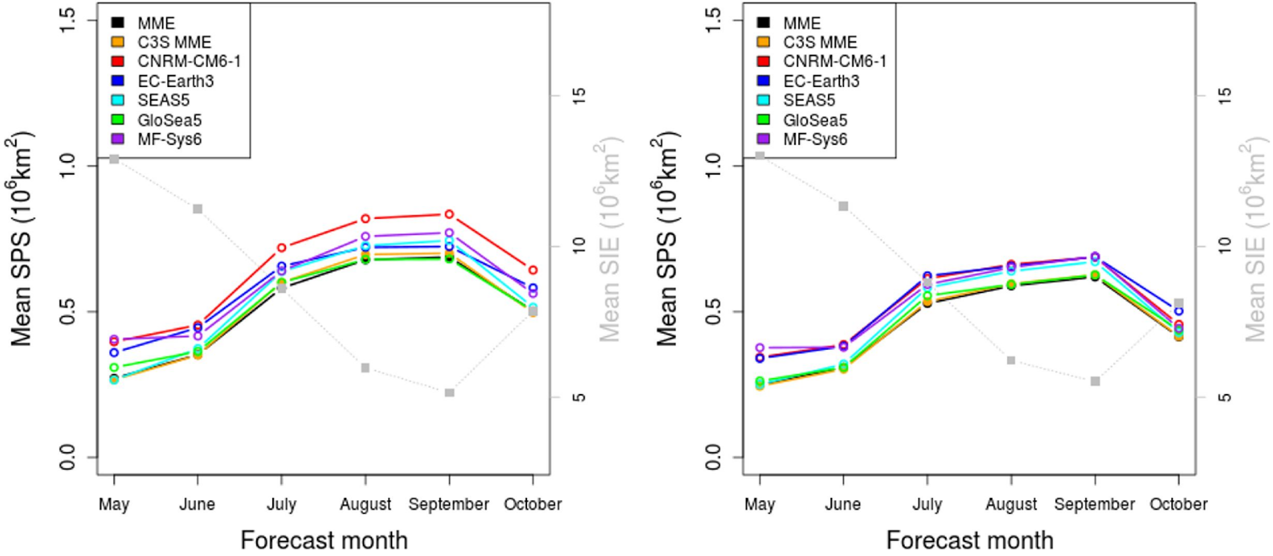
- Multi-model ensembles have the lowest IIEE due to model error compensation

- Trend-adjustment improves the IIEE of each individual system, but to various levels depending on the system (not shown here)



1993-2014 mean IIEE (ref : NSIDC) according to forecast month in stream 1 and Copernicus C3S re-forecasts initialized in May. Gridpoint SIC is linearly trend-adjusted before computation of IIEE.

Spatial Probability Score (SPS)



1993-2014 mean SPS (ref : NSIDC) according to forecast month in stream 1 and Copernicus C3S re-forecasts initialized in May. Probabilities are bias-corrected (left) and SIC is additionally linearly trend-adjusted (right) before computation of SPS.

- Confirms results with IIEE
- Very limited inter-annual variability of SPS
- SPS is much lower than IIEE for most systems → model spread in regions with high uncertainty and low skill is adequate

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Main conclusions / Future work (Part I)

- Results confirm previous work on limitations of current systems in predicting September sea ice from May starts

- Current state of the art systems outperform simple statistical approaches, although skill levels are limited

- Multi-model ensembles rank among the best systems for each forecast time

- Caveat : bias adjustment technique used → more elaborate methods (e.g. Dirkson et al. 2019)

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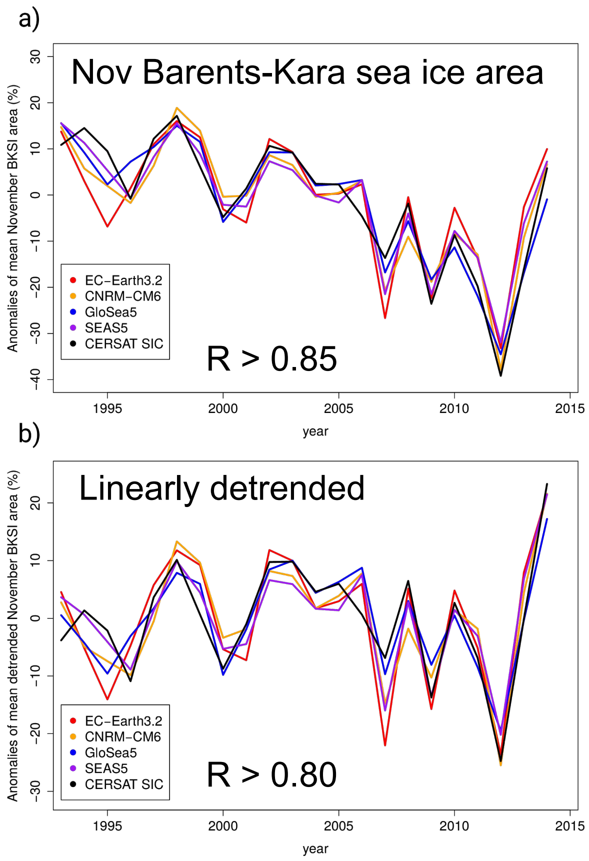
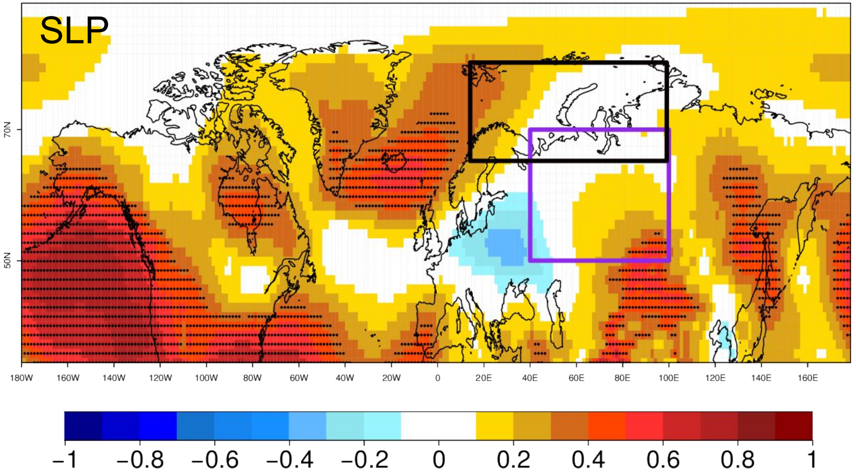
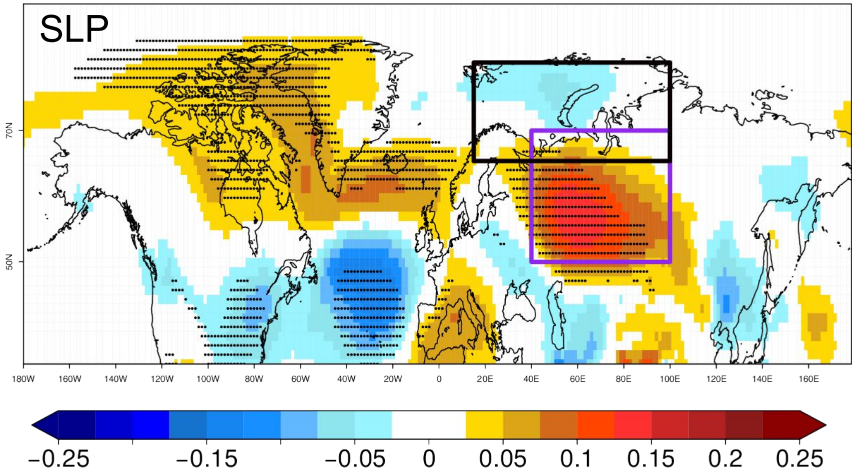
Methods (Part II)

- 1st set of forecasts: Retrospective winter re-forecasts from four seasonal forecast systems: EC-Earth3, CNRM-CM6-1, GloSea5 and SEAS5 (25 members each).
- Re-forecast period: 1993-2014, initialized close to the 1st November.
- PSL and TAS vs ERA-Interim, PR from GPCP v2.2.
- 2nd set of additional forecasts is synthetically built by removing the November Barents-Kara sea ice signal of the DJF sea level pressure, 2-meter temperature and precipitation fields from the 1st set of forecasts (using linear regression).



November Barents-Kara sea ice is linked to sea level pressure skill in northern Eurasia





\- Multi-system predictive skill +

\- Skill gain explained by BK sea ice +

Dots: Correlation coefficient is significantly different from zero with a 0.05 confidence. Ref: ERA-Interim

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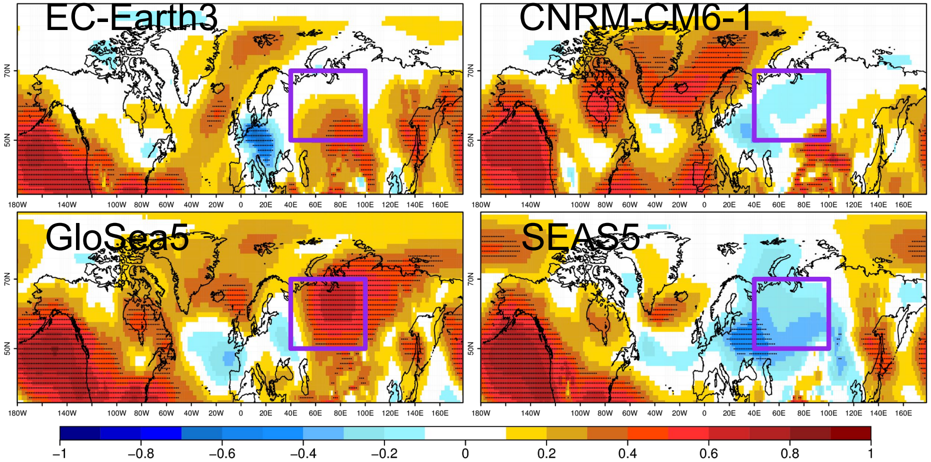
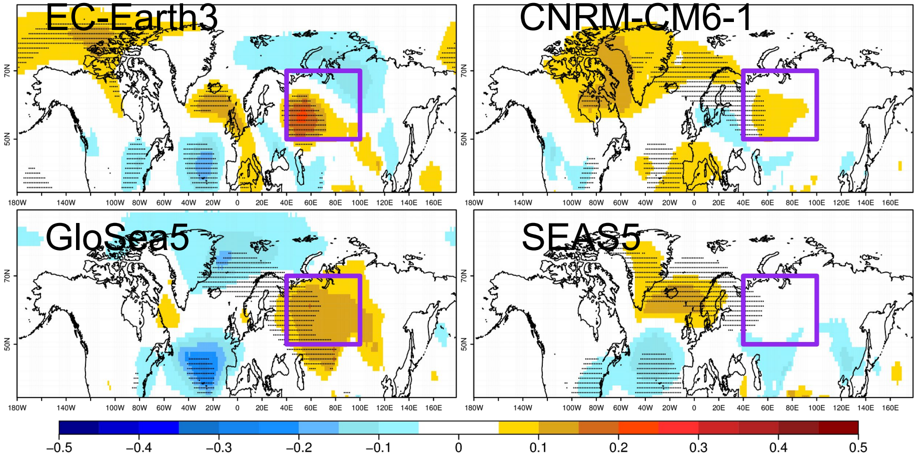
November Barents-Kara sea ice is linked to sea level pressure skill in northern Eurasia



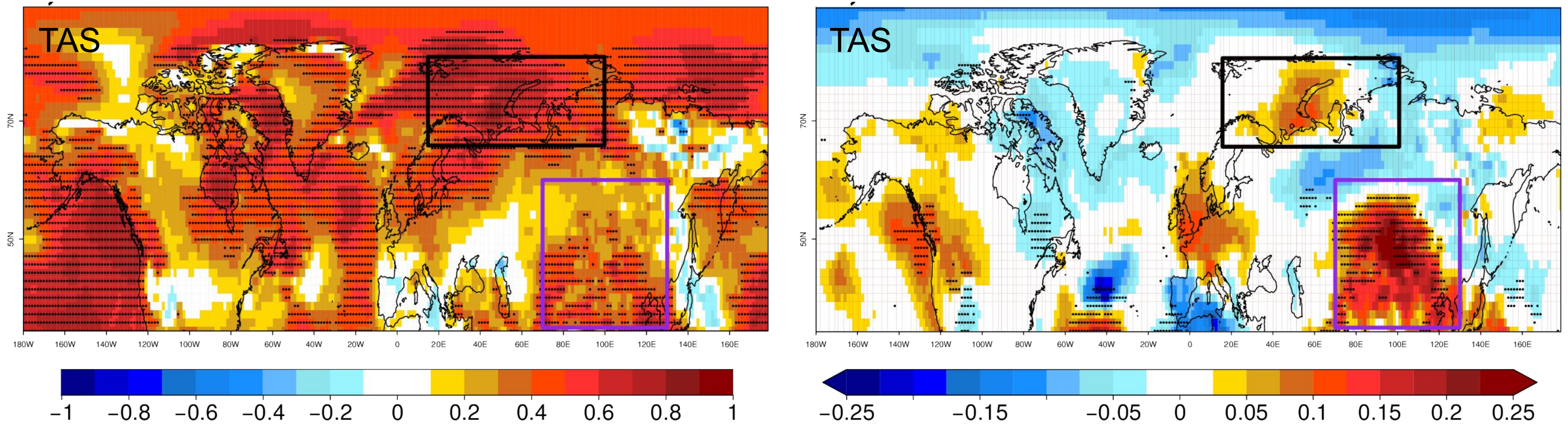


\- Multi-system predictive skill +

\- Skill gain explained by BK sea ice +

Dots: Correlation coefficient is significantly different from zero with a 0.05 confidence. Ref: ERA-Interim

November Barents-Kara sea ice is linked to surface temperature skill in northern Asia

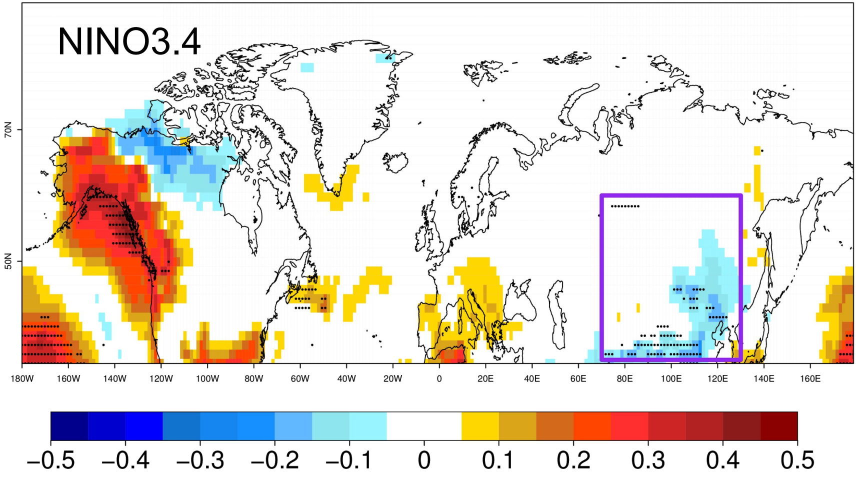


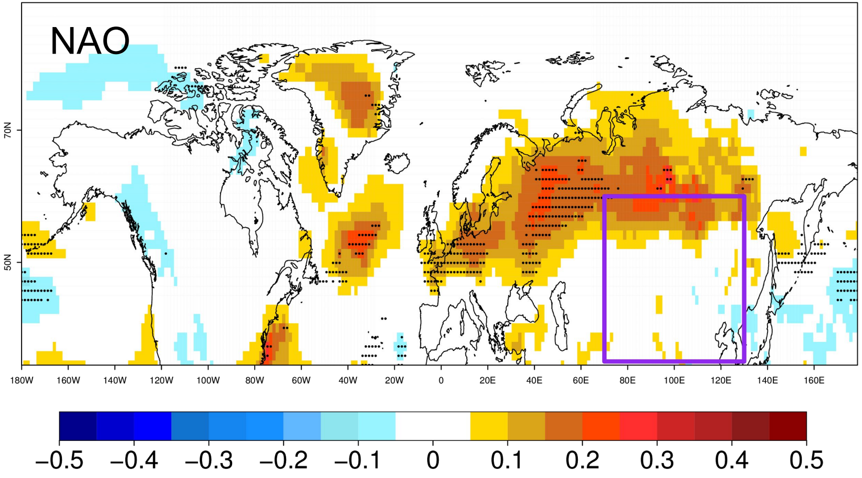
- Multi-system predictive skill +

- Skill gain explained by BK sea ice +

Dots: Correlation coefficient is significantly different from zero with a 0.05 confidence. Ref: ERA-Interim

November Barents-Kara sea ice effect on TAS comparable to DJF NAO and larger than Nov NINO3.4 (over Northern Eurasia)





\- Skill gain explained by Nov NINO3.4 +

\- Skill gain explained by DJF NAO +

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Dots: Correlation coefficient is significantly different from zero with a 0.05 confidence. Ref: ERA-Interim

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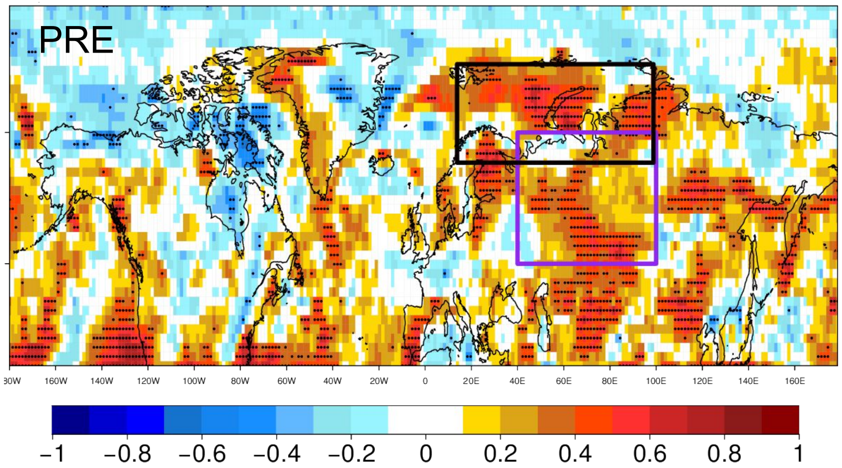
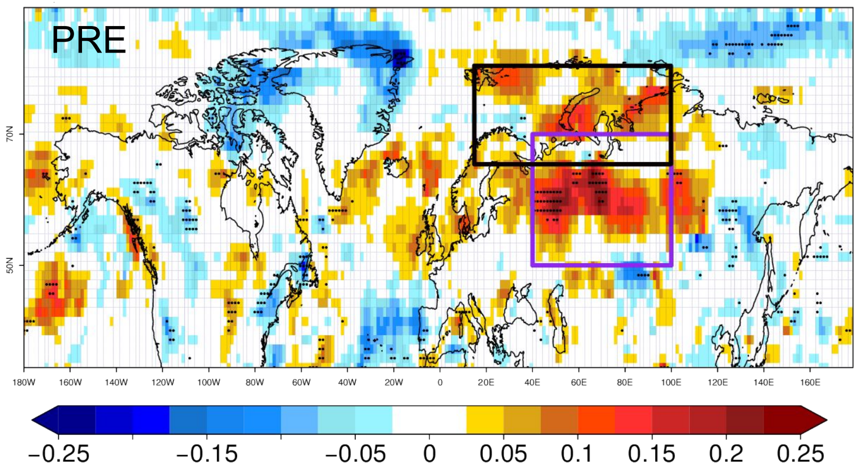
November Barents-Kara sea ice is linked to precipitation skill in northern Eurasia





\- Multi-system predictive skill +

\- Skill gain explained by sea ice +

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Dots: Correlation coefficient is significantly different from zero with a 0.05 confidence. Ref: GPCP2.2

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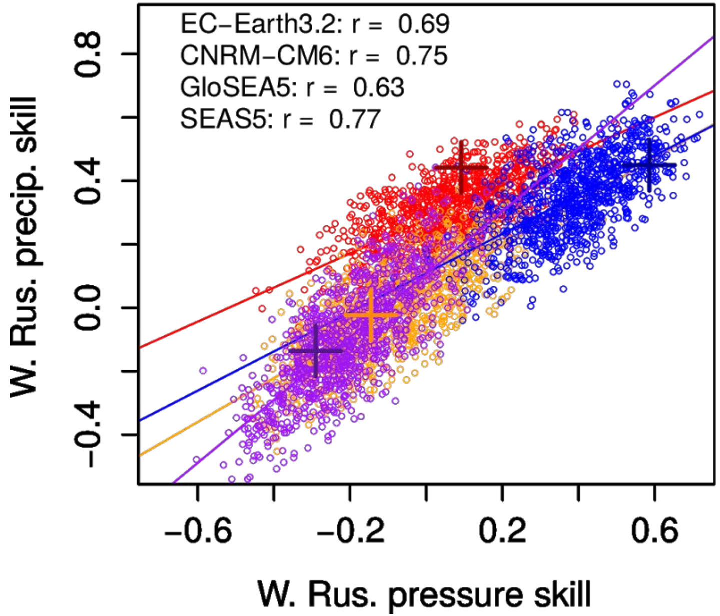
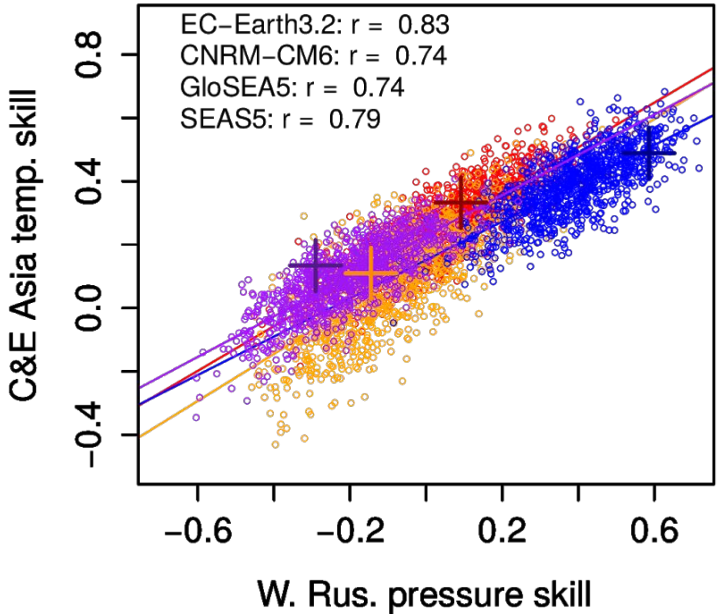
Skill in DJF surface temperature and precip. strongly linked to DJF sea level pressure skill





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Ref: ERA-Interim & and GPCP2.2

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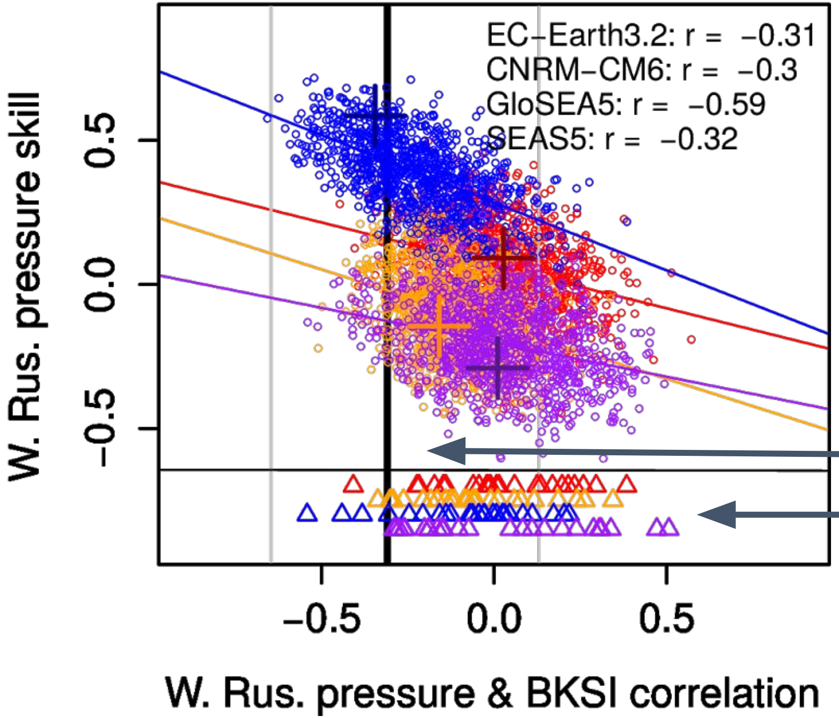
Eurasian sea level pressure skill linked to Barents-Kara sea ice?



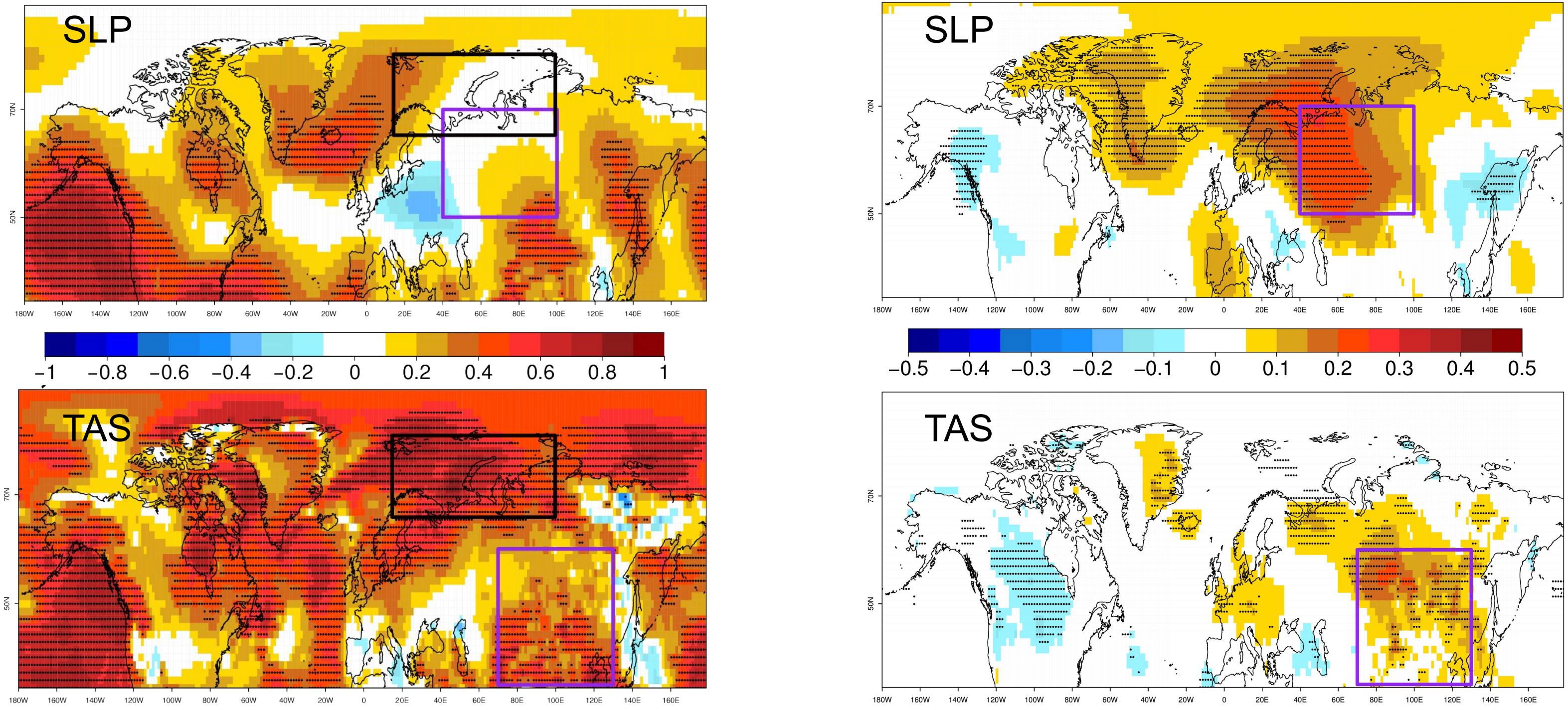
- Each circle represent values (for each system) from a 10-member mean randomly sampled from the 25-member ensemble.
- “Teleconnection strength”: correlation between November BKSI and DJF SLP skill in western Russia

Observed value

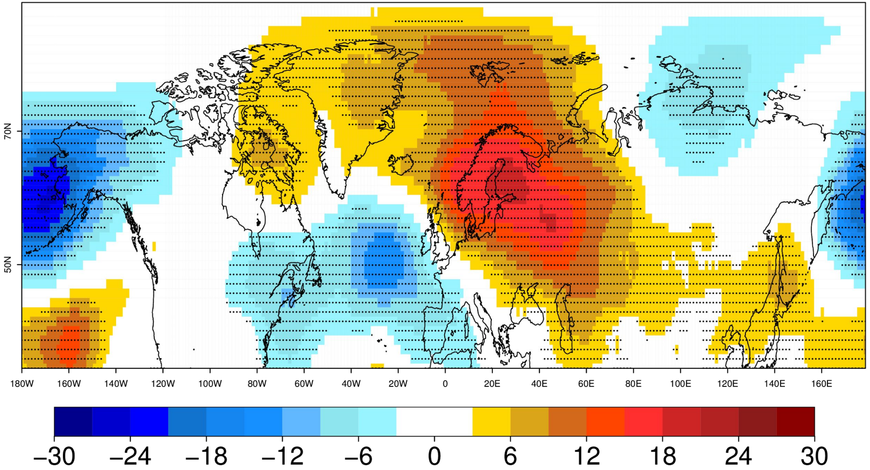
Individual members

“Teleconnection strength”

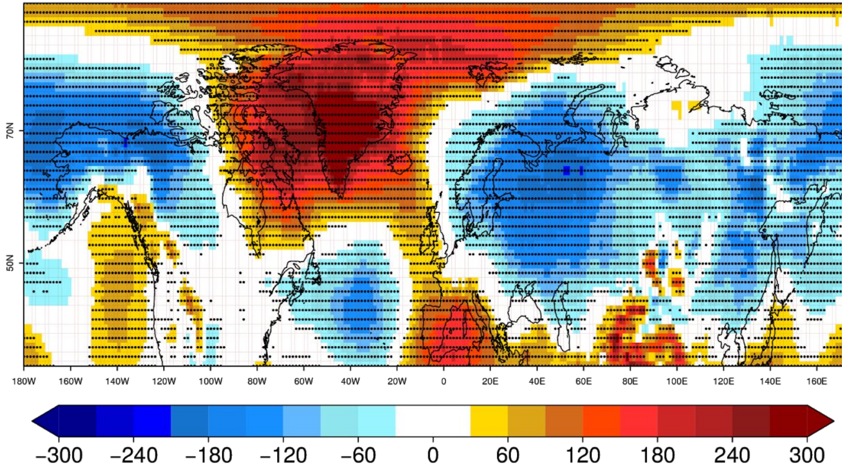
Skill improvement when selecting the top 10% subsets with strongest teleconnection



Members with Scandinavian Blocking in November favor Arctic - midlatitude linkages and reduce model systematic bias



Sea level pressure difference (Pa) between 10 member subsets with top and bottom 10% teleconnection strength



November Sea level pressure bias (Pa)

Dots: Correlation coefficient is significantly different from zero with a 0.05 confidence

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Summary (Part II)

- Climate forecast systems have limited predictive capacity at seasonal scales in the Northern Hemisphere mid-latitudes.
- Autumnal Barents and Kara Sea ice is likely a source of winter climate predictability in large regions of northern Eurasia.
- Analysis of large multi-model ensembles of climate predictions suggests that winter predictability in Eurasia is enhanced by a sea ice - atmosphere linkage.
- Systematic mode biases may reduce predictive capacity of forecasts systems.

Limitations:

- Short re-forecast period (1993-2014)
- Linear method applied to study a possible non-linear phenomenon.

Thank you

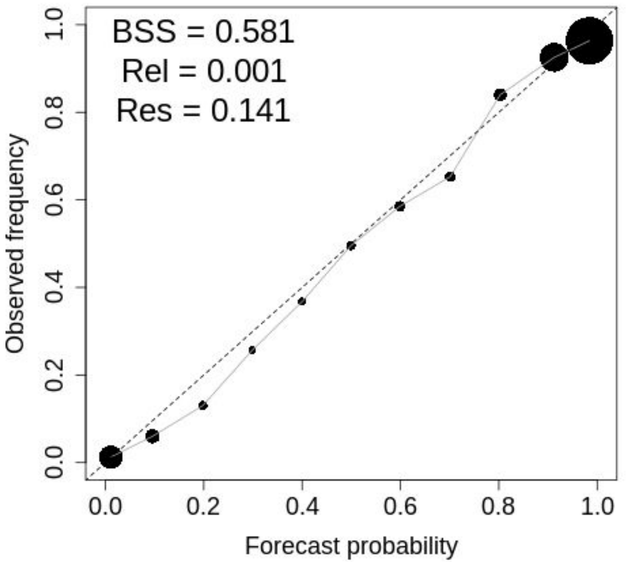
(Optional) : Beaufort-Chukchi reliability and Brier Skill Score

- Reliability diagram and Brier Skill Score

- Multi-model ensemble has improved reliability (model diversity + ensemble size effect)

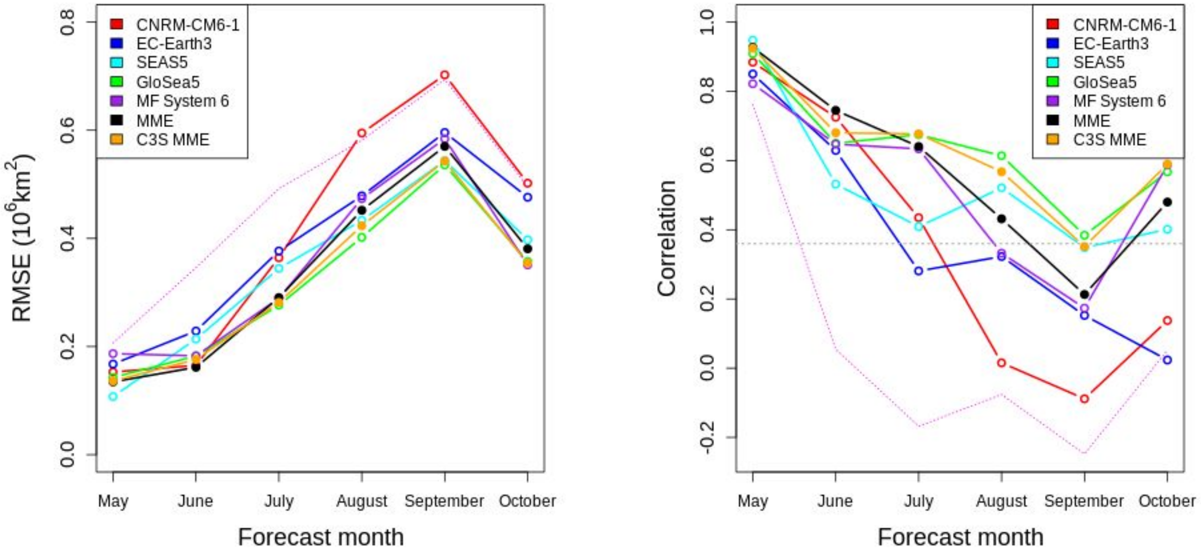
- High skill with respect to naïve probabilistic forecast based on climatology

- Trend adjustment improves results (not shown)



Reliability diagram for September 1993-2014 probability re-forecasts for SIC>0.15 over the Beaufort-Chukchi seas region, for the C3S multi-model ensemble (3 systems) after trend-adjustment.

SIE RMSE and correlation with NSIDC



SIE RMSE (left) and correlation (right) with NSIDC according to forecast month in stream 1 and Copernicus C3S re-forecasts initialized in May 1993-2014.

- Most systems clearly outperform persistence of April anomalies
- Results confirm spring predictability barrier for summer SIE → very few models show significant skill for September SIE
- Multi-model ensembles generally rank amongst the best systems

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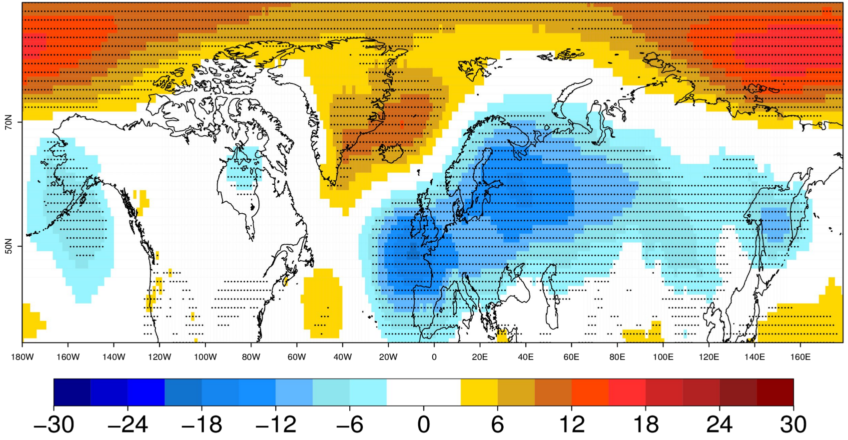
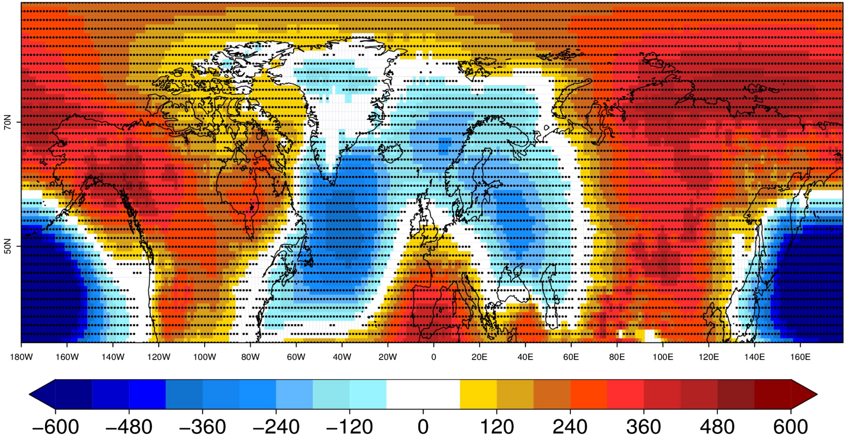
Not so clear in DJF if the Arctic - midlatitude linkage reduces model systematic bias



Sea level pressure difference (Pa) between 10 member subsets with top and bottom 10% teleconnection strength



DJF Sea level pressure bias (Pa)

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Dots: Correlation coefficient is significantly different from zero with a 0.05 confidence

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Can Arctic sea ice really affect mid-latitude weather?

nature climate change — LETTERS
https://doi.org/10.1038/s41558-018-0379-3

A reconciled estimate of the influence of Arctic sea-ice loss on recent Eurasian cooling

Masato Mori[1*], Yu Kosaka[1], Masahiro Watanabe[2], Hisashi Nakamura[1] and Masahide Kimoto[2]

Jan 2019

nature climate change — ARTICLES
https://doi.org/10.1038/s41559-019-0551-4

Minimal influence of reduced Arctic sea ice on coincident cold winters in mid-latitudes

Russell Blackport[1*], James A. Screen[1], Karin van der Wiel[2] and Richard Bintanja[2,3]

Aug 2019

nature COMMUNICATIONS

ARTICLE

DOI: 10.1038/s41467-018-02992-9 OPEN

Warm Arctic episodes linked with increased frequency of extreme winter weather in the United States

Judah Cohen[1,2], Karl Pfeiffer[1] & Jennifer A. Francis[3]

March 2018

nature climate change — REVIEW ARTICLE
https://doi.org/10.1038/s41558-019-0662-y

Divergent consensuses on Arctic amplification influence on midlatitude severe winter weather

J. Cohen[1,2*], X. Zhang[3], J. Francis[4], T. Jung[5,6], R. Kwok[7], J. Overland[8], T. J. Ballinger[9], U. S. Bhatt[3], H. W. Chen[10,11], D. Coumou[12,13], S. Feldstein[11], H. Gu[14], D. Handorf[5], G. Henderson[15], M. Ionita[5], M. Kretschmer[13], F. Laliberte[16], S. Lee[11], H. W. Linderholm[17,18], W. Maslowski[19], Y. Peings[20], K. Pfeiffer[1], I. Rigor[21], T. Semmler[5], J. Stroeve[22], P. C. Taylor[23], S. Vavrus[24], T. Vihma[25], S. Wang[14], M. Wendisch[26], Y. Wu[27] and J. Yoon[28]

December 2019

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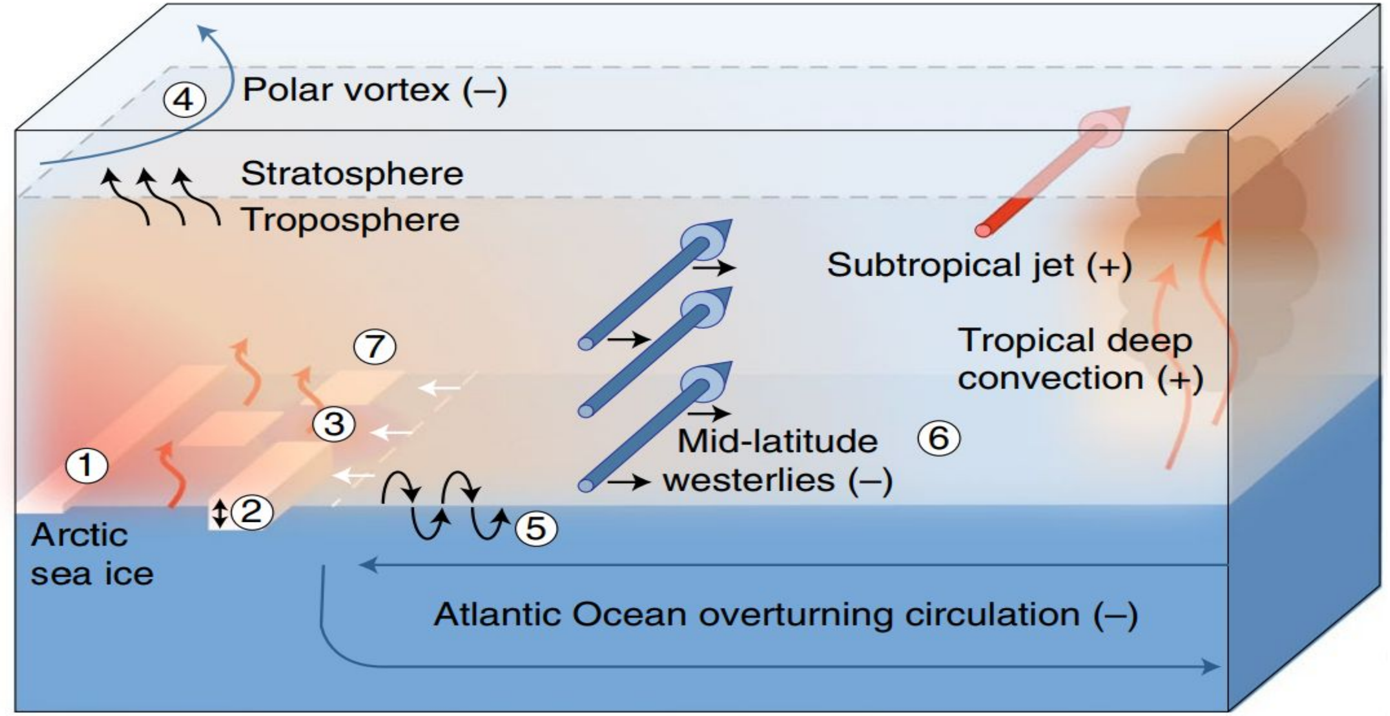
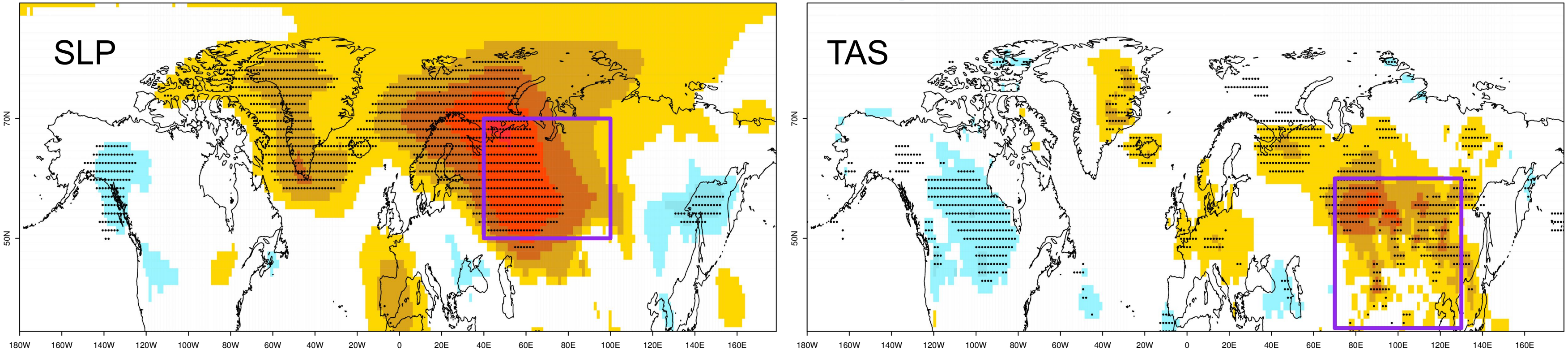
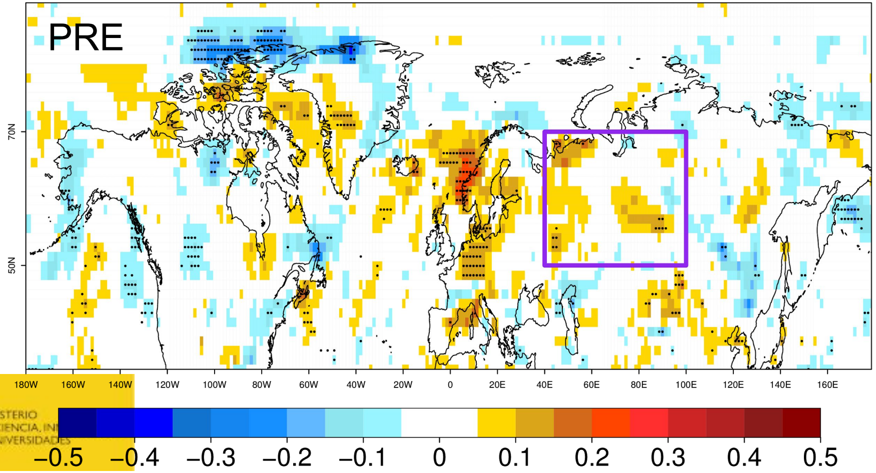
How can Arctic sea ice loss affect climate?



Screen et al. (2018)

Skill improvement when selecting the top 10% subsets with strongest teleconnection





Dots: Correlation coefficient is significantly different from zero with a 0.05 confidence

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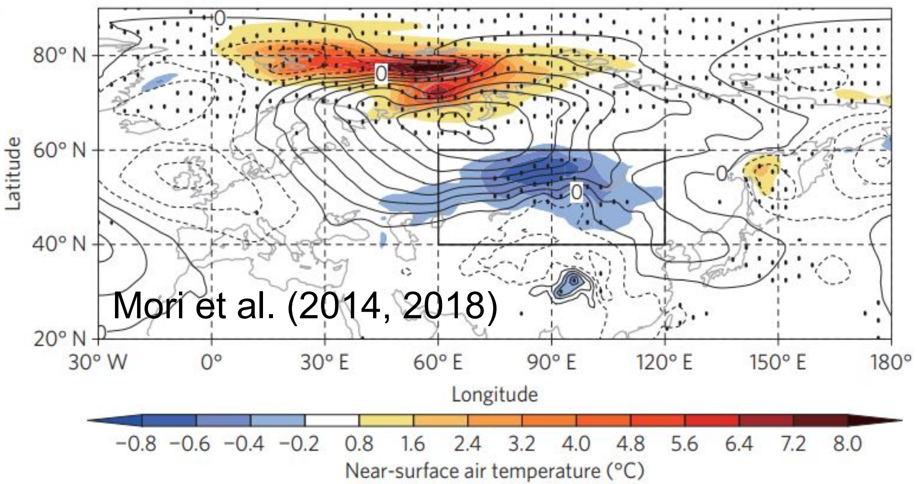
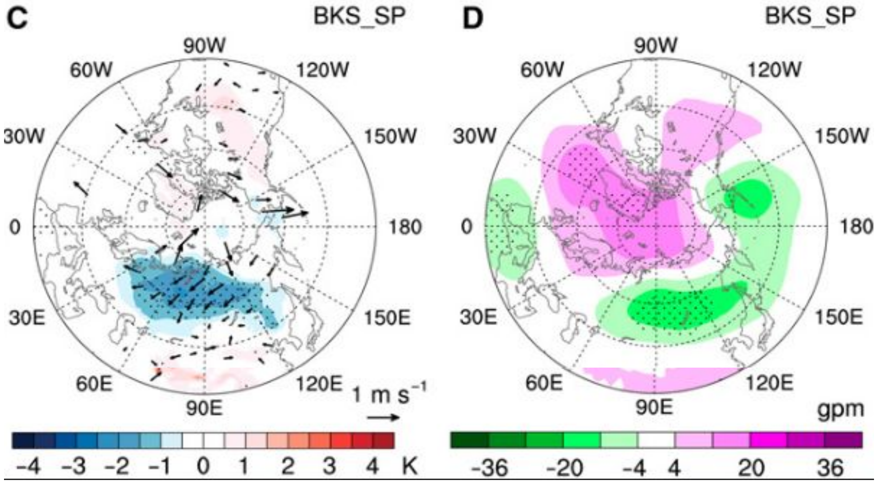
The Barents-Kara sea ice (BKSI) mechanism





Stratospheric pathway Zhang (2018)

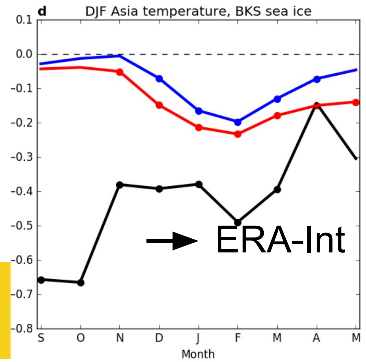
nature climate change

ARTICLES

https://doi.org/10.1038/s41558-019-0551-4

Minimal influence of reduced Arctic sea ice on coincident cold winters in mid-latitudes

Russell Blackport[1]*, James A. Screen[1], Karin van der Wiel[2] and Richard Bintanja[2,3]



Blackport et al. (2019)

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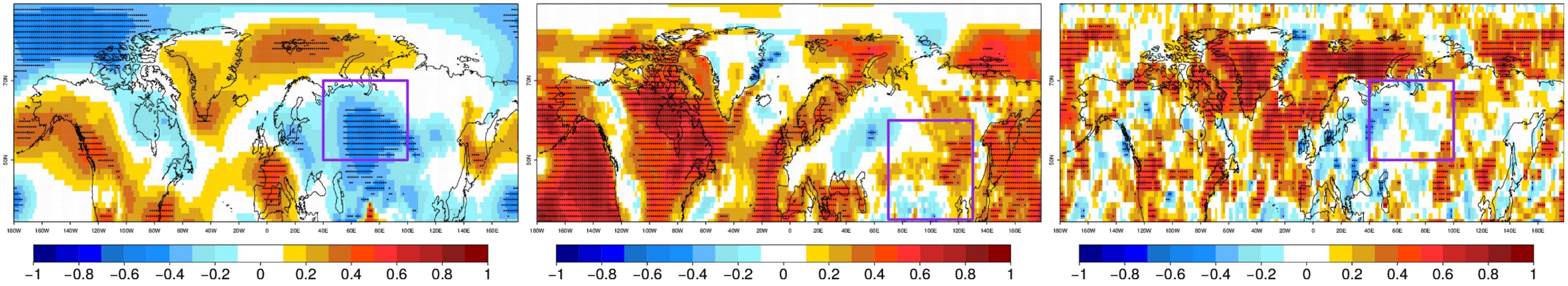
Dynamical seasonal forecasts beat simple persistence forecasts



\- Multi-system predictive skill +

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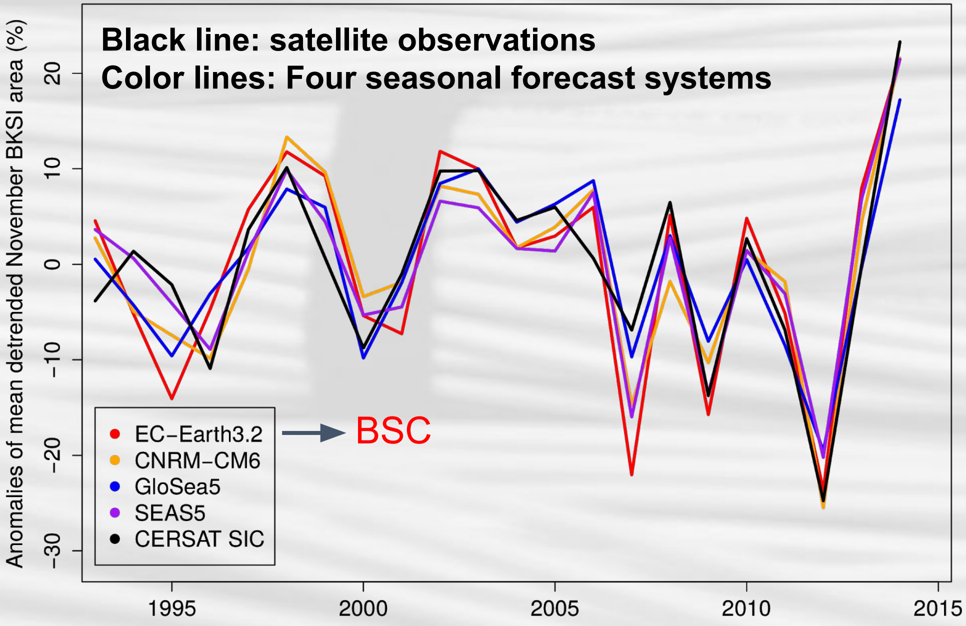
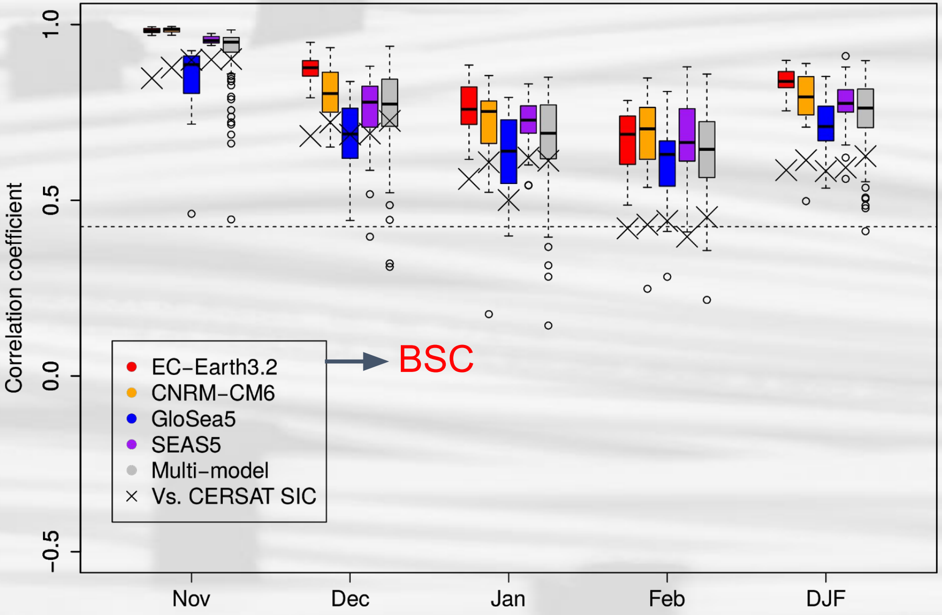
Dots: Correlation coefficient is significantly different from zero with a 0.05 confidence

Seasonal forecast of Barents-Kara sea ice





We use these series as Barents-Kara sea ice indices

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